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A Multi-Factor Machine Learning Framework for Gold Price Forecasting and Investment Decision Support

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Abstract- Gold price forecasting plays a crucial role in financial investment planning, portfolio diversification and risk management because of the volatile nature of global financial markets. Accurate prediction is challenging because gold prices are influenced by multiple economic, financial, geopolitical and market-related factors. This study proposes a multi-factor machine learning framework for gold price forecasting and investment decision support, integrating machine learning, deep learning, financial analytics, sentiment analysis and optimisation techniques. The framework uses macroeconomic indicators, market volatility, inflation rates, exchange rates, commodity prices and financial news sentiment to improve forecasting accuracy and support strategic investment decisions. Fourteen studies published between 2020 and 2026 are reviewed and organised into three themes covering machine learning and deep learning techniques, multi-factor analytics and financial indicator integration, and intelligent investment decision support. The reviewed evidence is consolidated into comparative tables that map each study to its data context, method, principal finding and contribution to the proposed design, and seven research gaps are identified and mapped to corresponding research directions. The framework is specified through five factor blocks and six predictive components including Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), CNN-LSTM, Support Vector Regression, Random Forest Regression and optimisation-based neural networks, together with a decision-support layer covering portfolio optimisation, risk assessment and adaptive forecasting. The findings indicate that multi-factor machine learning frameworks can enhance forecasting reliability, reduce prediction uncertainty and improve investment strategy optimisation in dynamic financial markets.

Keywords- Gold price forecasting; machine learning; deep learning; predictive analytics; investment decision support; financial analytics; multi-factor forecasting; LSTM; portfolio optimisation; risk management.

I. Introduction

Gold has historically been considered one of the most stable and valuable investment assets in global financial markets. It serves as a safe-haven commodity during economic crises, inflationary periods, geopolitical uncertainty and financial market instability. Investors and financial institutions monitor gold price movements closely because they significantly influence investment portfolios, wealth preservation strategies and risk management decisions.

Increasing volatility in global markets and the rapid growth of digital financial systems have created new challenges in forecasting gold prices accurately. Traditional methods such as econometric models and statistical regression face limitations in handling complex non-linear relationships, large-scale financial datasets and rapidly changing market dynamics. Researchers and analysts have therefore increasingly adopted machine learning and deep learning approaches to improve forecasting accuracy and investment decision-making.

Machine learning models such as Support Vector Regression (SVR), Random Forest Regression and ensemble learning techniques have proved effective at capturing latent market patterns in financial time-series data. Deep learning architectures including Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) and CNN-LSTM models learn temporal dependencies and sequential market behaviour more effectively than traditional statistical models.

Recent studies emphasise the importance of integrating multiple financial and economic factors into forecasting frameworks. Inflation rates, exchange rates, interest rates, commodity prices, climate risks, financial news sentiment and market volatility all influence gold price fluctuations, and combining feature engineering, sentiment analysis and predictive analytics enables more reliable prediction.

Beyond forecasting accuracy, modern investment systems increasingly emphasise decision-support capabilities such as portfolio optimisation, risk management, scenario analysis and adaptive investment strategy. Advances in optimisation algorithms, hybrid neural networks and real-time analytics have further enhanced predictive investment systems, which now support both short-term and medium-term planning.

Despite this progress, many existing studies focus on predictive model performance without adequately addressing investment decision support, portfolio optimisation and multi-factor integration within a unified managerial analytics framework. This study therefore proposes a multi-factor machine learning framework for gold price forecasting and investment decision support that integrates advanced predictive models, financial analytics, feature engineering, sentiment analysis and intelligent investment management systems.

1. Contributions of this Study

The study makes four contributions. First, it consolidates fourteen studies on gold price forecasting into a structured thematic review supported by comparative tables rather than narrative description alone. Second, it specifies the factor blocks that supply inputs to the proposed framework and links each block explicitly to the literature that motivates it. Third, it sets out the predictive components of the framework together with the analytical function each performs, so that method selection is justified rather than assumed. Fourth, it identifies seven research gaps and maps each to a corresponding research direction.

2. Organisation of the Paper

Section 2 reviews the literature across three themes and consolidates it in comparative tables. Section 3 presents the structure of the proposed framework. Section 4 sets out the research gaps. Section 5 concludes, and Section 6 details future work.

II. Literature Review

Gold price forecasting has become a critical area of financial analytics and investment research because of increasing volatility in global markets and the growing importance of gold as a safe-haven asset. Researchers have adopted machine learning, deep learning, econometric analysis and predictive analytics frameworks to improve prediction accuracy and support strategic investment decisions. This section reviews the literature across three themes: machine learning and deep learning techniques, multi-factor analytics and financial indicator integration, and intelligent investment decision support.

1. Machine Learning and Deep Learning Techniques for Gold Price Forecasting

Machine learning and deep learning techniques have improved forecasting accuracy by capturing non-linear market relationships and temporal dependencies. Mostaghim, Andalib and Azgomi (2026) proposed a hybrid forecasting framework combining the Marine Predator Algorithm with a cascade-forward neural network, and demonstrated that optimisation algorithms integrated with neural networks enhance forecasting stability and predictive performance in dynamic markets.

Baradaran, Bohlouli and Motlagh (2024) conducted a comparative study of GRU and CNN-LSTM models for gold price forecasting in the Iranian market, and found that deep learning architectures effectively capture sequential financial patterns and outperform traditional methods in volatile environments. Zainuddin and Rachmat (2026) demonstrated the effectiveness of LSTM networks in modelling multi-time-frame gold price movements and improving short-term and medium-term accuracy.

Satyawan et al. (2026) explored gold price prediction using Support Vector Regression and Random Forest Regression, and showed that ensemble and regression-based methods improve reliability by handling non-linear market relationships. Aruna et al. (2021) proposed a machine learning framework for predicting potential gold prices and emphasised the value of predictive analytics for investment decision-making. John and Nidhina (2024) investigated gold price forecasting using machine learning techniques and reported that advanced predictive models provide more reliable investment insight than conventional statistical methods.

Das et al. (2021) reviewed a decade of machine learning techniques for gold price forecasting and concluded that hybrid frameworks and deep learning architectures significantly improve prediction accuracy and investment analysis. As the only synthesis in the corpus, this study provides external corroboration for the hybrid design adopted here. Collectively, this theme indicates that machine learning and deep learning models provide robust and adaptive forecasting solutions, while sharing a common limitation: each evaluates model accuracy in isolation rather than in terms of the investment decisions the forecast is meant to inform.

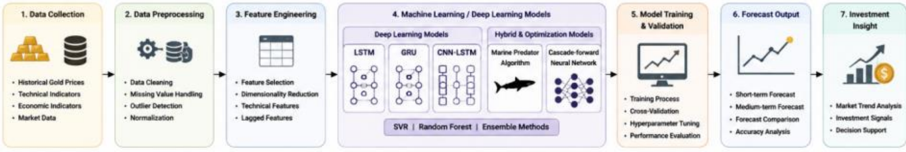

Figure 1: Deep learning and hybrid machine learning framework for gold price forecasting

Figure 1 illustrates a hybrid deep learning and machine learning framework for gold price forecasting. It integrates historical gold prices, financial indicators, preprocessing, feature engineering, neural architectures such as LSTM, GRU and CNN-LSTM, and optimisation algorithms including the Marine Predator Algorithm and ensemble regression methods, showing how these components improve forecasting accuracy for short-term and medium-term market analysis.

2. Multi-Factor Predictive Analytics and Financial Indicator Integration

A second stream emphasises integrating multiple economic and financial indicators into forecasting systems. Abou Mrad et al. (2026) proposed a framework combining feature engineering with financial news sentiment integration, and demonstrated that sentiment analysis and feature optimisation significantly improve predictive performance by incorporating market psychology and news dynamics. This is the only study in the corpus to operationalise sentiment as a forecasting input, which makes it the direct precedent for the sentiment block in Section 3.

Jahnavi, Bung and Reddy (2025) conducted a comprehensive study of gold price forecasting using predictive analytics, and highlighted the importance of combining macroeconomic indicators, big data analytics and machine learning models to improve precision and support strategic investment planning.

Khetan et al. (2024) analysed gold price forecasting and inflation trends in India and the United States using ARIMA and Holt-Winters models, and demonstrated that macroeconomic variables such as inflation and economic cycles significantly influence gold price behaviour. Lautier, Ling and Villeneuve (2026) examined price discovery mechanisms in gold markets and emphasised the role of market dynamics, investor expectations and global economic conditions in determining price movements.

Gupta and Banerjee (2025) explored forecast quality and alpha generation in machine learning gold timing systems, and demonstrated that forecast quality, trend-following strategy and bias reduction are essential for improving investment decision-making and portfolio performance. Dzerjinski, Pronina and Dzerjinskaya (2020) investigated long-term global gold production dynamics and highlighted the influence of supply-side factors on long-run price trends, introducing a determinant absent from every other study in the corpus. Together, this theme demonstrates that integrating macroeconomic indicators, sentiment, volatility, production dynamics and feature engineering enhances forecasting accuracy and investment analysis.

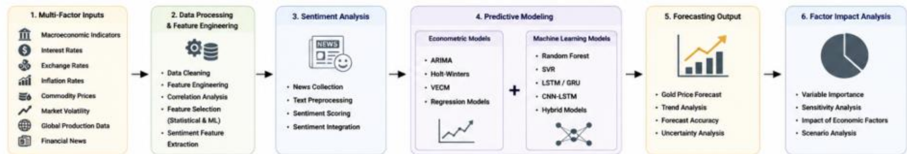

Figure 2: Multi-factor financial analytics model for gold price prediction

Figure 2 presents a multi-factor predictive analytics framework integrating macroeconomic indicators, inflation rates, exchange rates, commodity prices, financial news sentiment, market volatility and global production dynamics into gold price forecasting. It illustrates how feature engineering, sentiment analysis, econometric modelling and machine learning analyse the influence of multiple financial variables on price movements.

3. Intelligent Investment Decision Support and Forecast Optimisation

The evolution of predictive analytics has enabled decision-support systems that integrate forecasting models with portfolio management and risk assessment. Singha, Aguilera-Toste and Lahiri (2025) introduced a benchmark-neutral alpha forecasting framework for gold futures covering 2015 to 2025, and demonstrated that predictive analytics systems can generate high-capacity investment signals and improve portfolio management performance.

Recent work in this area emphasises real-time analytics, adaptive learning and forecasting optimisation, with feature selection, sentiment-driven forecasting and ensemble approaches used to improve reliability and reduce prediction uncertainty. Managerial analytics systems also integrate predictive outputs with risk management, portfolio diversification and scenario analysis so that investors can evaluate market conditions dynamically and optimise asset allocation.

This theme is the thinnest in the corpus, containing a single primary study. That imbalance is itself a finding: forecasting methodology is well served in the literature while the translation of forecasts into managerial decisions is not. Existing work still lacks a comprehensive multi-factor managerial analytics framework integrating deep learning, feature engineering, sentiment analytics, macroeconomic indicators and investment decision support into a unified environment, and few studies evaluate how forecasting frameworks improve investor decision-making, portfolio optimisation and risk management.

Figure 3: Intelligent investment decision support system for gold market forecast optimisation

Figure 3 depicts an intelligent decision-support framework integrating predictive forecasting models, portfolio optimisation, risk assessment, adaptive learning and real-time market analytics for gold investment management. It shows how predictive intelligence, scenario analysis and financial optimisation tools help investors improve portfolio performance, reduce risk and make strategic decisions under uncertain market conditions.

4. Consolidated Summary of the Reviewed Literature

Table 1 organises the reviewed studies by theme, and Table 2 compares each study on data context, method, principal finding and the specific contribution it makes to the design of the proposed framework.

Table 1: Thematic organisation of the reviewed literature

Theme	Analytical focus	Studies	Count
T1. Machine learning and deep learning techniques	Sequential and ensemble modelling of price series using LSTM, GRU, CNN-LSTM, SVR, Random Forest and optimisation-based networks	Mostaghim et al. (2026); Baradaran et al. (2024); Zainuddin & Rachmat (2026); Satyawan et al. (2026); Aruna et al. (2021); John & Nidhina (2024); Das et al. (2021)	7
T2. Multi-factor analytics and indicator integration	Feature engineering, news sentiment, macroeconomic drivers, price discovery and production dynamics	Abou Mrad et al. (2026); Jahnavi et al. (2025); Khetan et al. (2024); Lautier et al. (2026); Gupta & Banerjee (2025); Dzerjinski et al. (2020)	6
T3. Intelligent investment decision support	Translation of forecasts into portfolio signals, risk assessment and capacity analysis	Singha et al. (2025)	1

Table 2: Comparative summary of the reviewed studies

Study	Data context	Method	Principal reported finding	Contribution to the proposed framework
Mostaghim et al. (2026)	Global gold price	Marine Predator Algorithm with cascade-forward neural network	Optimisation-integrated networks improve stability and accuracy	Direct precedent for the optimisation-based network component
Baradaran et al. (2024)	Iranian gold market	GRU vs CNN-LSTM comparison	Deep architectures outperform traditional methods in volatile markets	Justifies the GRU and CNN-LSTM components
Zainuddin & Rachmat (2026)	Gold prices, multiple time frames	LSTM	LSTM improves short-term and medium-term forecast accuracy	Direct precedent for the LSTM component and horizon design

Study	Data context	Method	Principal reported finding	Contribution to the proposed framework
Satyawan et al. (2026)	Gold price prediction	Support Vector Regression and Random Forest Regression	Regression and ensemble methods handle non-linear relationships well	Justifies the SVR and Random Forest components
Aruna et al. (2021)	Gold prices	Machine learning prediction framework	Predictive analytics supports investment decision-making	Establishes the machine learning baseline
John & Nidhina (2024)	Gold prices	Machine learning forecasting techniques	Advanced models give more reliable insight than statistical methods	Reinforces the case for the ML component set
Das et al. (2021)	Decade-long review	Literature synthesis	Hybrid frameworks and deep architectures improve accuracy	Corroborates the hybrid framework design
Abou Mrad et al. (2026)	Gold prices with financial news	Feature engineering plus news sentiment integration	Sentiment and feature optimisation significantly improve accuracy	Sole precedent for the sentiment factor block
Jahnavi et al. (2025)	Gold price forecasting	Predictive analytics with macroeconomic indicators	Combining macro indicators with ML improves precision	Supports the macroeconomic factor block
Khetan et al. (2024)	India and US gold and inflation	ARIMA and Holt-Winters	Inflation and economic cycles significantly affect gold prices	Justifies inflation and rate variables; provides econometric benchmark
Lautier et al. (2026)	Gold markets	Price discovery analysis	Market dynamics and investor expectations drive price formation	Supports market expectation and volatility variables
Gupta & Banerjee (2025)	Gold timing system	Alpha decomposition and bias analysis	Forecast quality and bias control determine real performance	Imposes bias control as an evaluation requirement
Dzerjinski et al. (2020)	World gold production, long horizon	Long-term production dynamics analysis	Supply-side production patterns influence long-run price trends	Sole basis for the supply and production factor block
Singha et al. (2025)	Gold futures, 2015-2025	Benchmark-neutral alpha forecasting	Predictive systems generate high-capacity investment signals	Direct precedent for the decision-support layer

Three observations follow from Table 2. First, the corpus is methodologically deep but evaluation-narrow: nearly every study reports accuracy metrics and only Gupta and Banerjee (2025) tests whether apparent accuracy survives bias control. Second, coverage of the factor set is fragmented, with sentiment, macroeconomic drivers and production dynamics each addressed by a single study rather than jointly. Third, only one study addresses the translation of forecasts into investment decisions, which is the specific gap this framework targets.

III. Structure of the Proposed Framework

The proposed framework organises the factors and techniques described above into a single multi-factor structure. This section states its factor blocks, its predictive components and its decision-support layer; empirical estimation and validation lie outside the scope of the present study and are set out as future work in Section 6.
3.1 Factor Blocks and Input Variables

Table 3 specifies the five factor blocks that supply inputs to the framework, together with the variables in each block and the reviewed studies that motivate their inclusion. Organising inputs into blocks rather than a flat variable list allows the contribution of each category to be assessed separately during feature selection and model evaluation.

Table 3: Factor blocks and input variables of the proposed framework

Factor block	Input variables	Supporting studies
F1. Historical price and market series	Historical gold prices, time-series lags, trading activity	Zainuddin & Rachmat (2026); Baradaran et al. (2024); Satyawan et al. (2026)
F2. Inflation and monetary variables	Inflation rates, exchange rates, interest rates	Khetan et al. (2024); Jahnavi et al. (2025)
F3. Commodity prices and market volatility	Commodity prices, volatility measures, investor expectations	Lautier et al. (2026); Gupta & Banerjee (2025)
F4. Financial news sentiment	News sentiment scores, market psychology indicators	Abou Mrad et al. (2026)
F5. Supply and production dynamics	Global gold production patterns and supply-side indicators	Dzerjinski et al. (2020)

2. Predictive Components
Table 4 lists the predictive components incorporated in the framework and the analytical function each performs. The set is deliberately mixed: regression and ensemble methods provide interpretable benchmarks on engineered features, recurrent and convolutional-recurrent architectures represent temporal structure, and optimisation-based networks tune model parameters under volatile conditions.

Table 4: Predictive components and their analytical function

Component	Function within the framework	Rationale for inclusion
Support Vector Regression	Non-linear regression on engineered macroeconomic and sentiment features	Effective on moderate-sized structured financial datasets
Random Forest Regression	Ensemble prediction and relative importance of factor blocks	Robust to correlated indicators and provides feature attribution
LSTM networks	Modelling sequential dependence across multiple forecast horizons	Demonstrated effectiveness on gold price series
GRU networks	Sequential modelling with a lighter parameterisation than LSTM	Comparable accuracy at lower computational cost
CNN-LSTM	Extracting local patterns before sequential modelling	Reported to outperform single-architecture models in volatile markets
Optimisation-based neural networks	Parameter tuning via metaheuristic optimisation	Improves forecasting stability under changing market conditions

3. Decision-Support Layer
The framework's final layer translates forecasts into investment actions through portfolio optimisation, risk assessment and adaptive forecasting analytics, following the direction indicated by Singha et al. (2025). This layer is what distinguishes the framework from the accuracy-focused studies in Table 2, and is the component for which the literature currently offers the least guidance.

Consistent with Gupta and Banerjee (2025), evaluation is treated as a design requirement rather than a reporting step: predictive components must be assessed with strict separation of training and evaluation data so that reported gains are not an artefact of look-ahead bias. Interpretability is a parallel requirement, since investors need to understand which factors drive a forecast before acting on it.

IV. Research Gap

Although substantial research has been conducted on gold price forecasting using machine learning and econometric approaches, seven gaps remain in the current literature. They are stated below and mapped to corresponding research directions in Table 5.

First, many traditional forecasting studies rely heavily on statistical and econometric models such as ARIMA and Holt-Winters methods, which struggle to capture non-linear relationships and rapidly changing dynamics in gold market behaviour.

Second, although techniques such as LSTM, GRU, CNN-LSTM, SVR and Random Forest Regression have improved predictive accuracy, many studies focus on forecasting performance without integrating predictive outputs into investment decision-support systems and portfolio optimisation frameworks.

Third, most forecasting models use limited input variables and fail to integrate macroeconomic indicators, commodity prices, inflation rates, exchange rates, market volatility, climate risks and financial news sentiment into a unified multi-factor framework.

Fourth, limited research explores the integration of feature engineering, sentiment analysis, optimisation algorithms and adaptive learning mechanisms into forecasting systems capable of responding dynamically to changing market conditions.

Fifth, many advanced predictive models operate as opaque systems with limited interpretability. Investors and analysts require understandable predictive insight, factor-impact analysis and scenario evaluation tools to support confident decisions and effective risk management.

Sixth, existing studies rarely combine predictive forecasting, portfolio diversification, risk optimisation and investment strategy evaluation into a comprehensive managerial analytics and decision-support ecosystem.

Finally, there is limited research evaluating how machine learning-based forecasting frameworks influence investor behaviour, portfolio performance and strategic financial planning under uncertain global market conditions.

Table 5: Research gaps mapped to corresponding research directions

No.	Identified research gap	Corresponding research direction
G1	Reliance on linear econometric specifications	Benchmark non-linear and sequential models against ARIMA and Holt-Winters on identical gold price data
G2	Accuracy prioritised over investment application	Evaluate forecasts by portfolio and risk outcomes, not error metrics alone
G3	Limited input variable coverage	Estimate a unified multi-factor model spanning all five factor blocks in Table 3
G4	Feature engineering, sentiment and adaptive learning not integrated	Combine feature optimisation, sentiment inputs and online updating in one pipeline
G5	Models operate as opaque systems	Apply explainable AI and report factor-impact and scenario analysis alongside accuracy
G6	Forecasting not combined with portfolio and risk management	Integrate diversification, risk optimisation and strategy evaluation into the decision-support layer

No.	Identified research gap	Corresponding research direction
G7	Investor-level outcomes not evaluated	Assess effects on investor behaviour, portfolio performance and strategic planning under uncertainty

V. Conclusion

Gold price forecasting has become increasingly important for investors, financial institutions and policymakers because of rising financial uncertainty, inflationary pressure and market volatility. Advances in machine learning, deep learning, predictive analytics and financial optimisation have improved the capacity to analyse gold market behaviour and forecast future price movements.

This study proposed a multi-factor machine learning framework for gold price forecasting and investment decision support, integrating machine learning models, deep learning architectures, feature engineering, sentiment analysis, financial analytics and intelligent decision-support systems into a unified structure. The framework was specified through five factor blocks, six predictive components and a decision-support layer, each linked explicitly to the reviewed literature that motivates its inclusion.

The review of fourteen studies demonstrates that LSTM, GRU, CNN-LSTM, SVR, Random Forest Regression and optimisation-based neural networks effectively capture temporal dependencies and non-linear relationships in financial data, and that integrating macroeconomic indicators, market sentiment and production dynamics enhances predictive performance. It also shows that the literature evaluates forecasts almost entirely on accuracy metrics, that only one reviewed study addresses look-ahead bias, and that only one addresses the translation of forecasts into investment decisions. The framework contributes to academic research and financial management practice by connecting forecasting accuracy with investment decision support, and by specifying what an integrated multi-factor gold forecasting system would need to contain. Its principal limitation is that it is presented as a design rather than an estimated model; empirical validation is required before claims about forecasting accuracy can be made.

Future Work

Future research can extend this study in several directions, presented here in order of priority. First, the framework should be empirically validated using large-scale real-time gold market datasets from international commodity exchanges, with forecasting accuracy assessed out of sample and under strict controls against look-ahead bias.

Second, advanced techniques including reinforcement learning, transformer-based architectures, graph neural networks, federated learning and generative AI should be benchmarked against the components in Table 4 so that any accuracy gain can be weighed against the loss of interpretability.

Third, real-time financial news analytics, social media sentiment analysis, geopolitical event monitoring, investor psychology analysis and multimodal financial data should be tested as supplementary inputs, with attention to whether they add incremental predictive value beyond the factor blocks in Table 3.

Fourth, additional macroeconomic and environmental factors including climate risk, energy prices, cryptocurrency interactions, central bank policy and global uncertainty indicators should be incorporated to extend the multi-factor design.

Fifth, explainability and transparency should be advanced through explainable AI, interpretable forecasting models and interactive visualisation dashboards that help investors understand predictive outputs and factor influences.

Finally, longer-term work may develop intelligent financial ecosystems integrating predictive forecasting, automated trading, portfolio optimisation, risk management, personalised investment recommendation and real-time decision-support analytics into a comprehensive investment management platform.

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